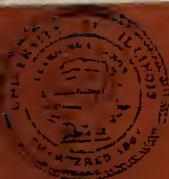


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Planning System Success: Towards
Developing and Testing an Operational Model

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Planning System Success: Towards
Developing and Testing an Operational Model

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PLANNING SYSTEM SUCCESS: TOWARDS
DEVELOPING AND TESTING AN OPERATIONAL MODEL

ABSTRACT

A measurement model of Planning System Success is proposed and validated using Jöreskog's analysis of covariance structures approach and data from 202 leading North American corporations. Two dimensions--viz., improvements in the capabilities of the planning system and the extent of fulfillment of key planning objectives--are developed and their convergent and discriminant validities are demonstrated. Validated measurement schemes for these dimensions are offered for use in future research on the effectiveness of strategic planning.

KEY WORDS: policy/planning, statistics, measurement models, and scales for strategic planning effectiveness.

In much of the research on strategic planning systems, the attention given to operationalization and measurement issues has been woefully inadequate. The degree to which a firm is "formalized" in its strategic planning practices, for example, has been typically operationalized in terms of categorical variables such as "planner vs. non-planner" (cf. Thune & House, 1970; Karger & Malik, 1975) or "programmed vs. impoverished" planner (cf. Fulmer & Rue, 1973). Such classifications have neither the required discriminatory power (Kudla, 1980) nor are generally reliable and valid (Nunnally, 1978).

Similarly, the benefits of strategic planning have been typically evaluated using financial criteria such as Return on Investment, Return on Equity, etc. (cf. Thune & House, 1970), although many conceptual writings on strategic planning have emphasized the non-financial benefits (cf. Camillus, 1975; Steiner, 1979) or the "process" benefits of planning (cf. King & Cleland, 1978; King, 1983). As Wood and LaForge (1979) remarked, "It is time to...abandon the smorgasbord use of financial measures as dependent variables and to try to match up the appropriate performance criteria with the primary objectives of the organization being studied" (p. 526). It is increasingly recognized that more rigorous operationalizations of the complex constructs involved in strategic planning systems research is a necessary prerequisite for theory development and testing in this area.

This paper reports the results of a study aimed at developing and testing an operational model of the benefits or success of strategic planning. Development of the model, which includes a broad array of indicators reflecting planning system success is first discussed. Next,

the results of testing this model using data on the strategic planning practices of 202 planning units are presented. Finally, the potential use of this model for other researchers interested in furthering strategic planning systems research is elaborated.

DEVELOPING AN OPERATIONAL MODEL OF PLANNING SYSTEM SUCCESS

Planning System Success is conceptualized in terms of two distinct, but interrelated dimensions--one, the extent of improvement in the capabilities of the planning system to effectively deliver the support for strategic decision-making, and the other, the extent of fulfillment of key planning objectives. The theory underlying these two interconnected dimensions of the model are discussed in the following paragraphs, while Figure 1 depicts the overall operational model.

INSERT FIGURE 1 ABOUT HERE

Improvement in the Capabilities of Planning System (CAPABILITIES)

A planning system can be visualized as a broadly-defined administrative system which provides support for the efficient and effective management of the enterprise. The capabilities of the system then become the key influences on its effectiveness. In a review and critique of the appropriateness of various measures of planning effectiveness, Lorange noted that, "... many [of these] measures were based on some surrogate variable, when it probably would have been more relevant to measure effectiveness as a function of how well the formal planning system's capabilities were able to meet the specific planning needs ..." (1979, p. 230, emphasis added).

Ideally, the system's capabilities should be considered in relation to the specific needs of the context. However, a broad conceptualization of a system's major capabilities is developed here for large-scale comparative studies by focussing on a few generic capabilities of planning systems, which have been emphasized in normative and descriptive writings on strategy and strategic planning. These capabilities are required of nearly every formal administrative system. They include, but are not limited to, the system's ability to anticipate surprises and crises (Ansoff, 1975), its flexibility to adapt to a dynamic environment (Thompson, 1967), ability to facilitate effective management control (Anthony, 1965; Lorange & Vancil, 1977), its role in the identification of new business opportunities (Steiner, 1979), as well as its ability to enhance creativity and innovation (Taylor & Hussey, 1982).

Based on a review of the literature on strategic planning, 12 key capabilities tapping the above requirement areas were identified. This list was presented to a group of 15 senior-level planning executives who participated in a seminar on strategic planning at the university. This enabled us to assess the "content" validity of the concept, as well as to ensure that these indicators were largely context-free. Such an exercise confirmed that the list was reasonably comprehensive as perceived by planning executives, and that the description of the items was understandable and unambiguous. The list of the 12 items of CAPABILITIES is provided in Table 1.

INSERT TABLE 1 ABOUT HERE

Extent of Fulfillment of Planning Objectives (OBJECTIVES)

While the degree of improvement in the system's CAPABILITIES reflect the process dimension of the concept of planning system success, this dimension is intended to tap the outcome benefits of planning. Six key objectives of planning make up the OBJECTIVES dimension.

Planning aims to fulfill both tangible and intangible objectives (King & Cleland, 1978; Lorange, 1980; Lorange & Vancil, 1977; Steiner, 1979). Using a goal model of planning success or planning effectiveness, the ultimate success of strategic planning can be expected to be reflected in the extent of fulfillment of key planning objectives. These include predicting future trends (Paul, Donavan & Taylor, 1978), enhancing management development through the educational value of the planning process (Hax & Majluf, 1984), evaluating alternatives based on more relevant information (King & Cleland, 1978), as well as improvements in financial performance. Here again, the focus was on identifying context-free planning objectives with a balanced mix of both financial and non-financial objectives. The list of six important planning objectives is shown in Table 2.

INSERT TABLE 2 ABOUT HERE

TESTING THE OPERATIONAL MODEL

In the previous section, an operational model of planning system success, with two interrelated dimensions, was conceptually developed. Such a model is not operationally useful unless it is tested against data to establish its measurement properties. The appropriateness of the proposed model's theoretical structure is evaluated using

Jöreskog's analysis of covariance structures (Jöreskog, 1969; 1971; Jöreskog & Sörbom, 1978; 1979). Basically, the analysis of covariance structures enables one to test the degree of correspondence between the theoretical model(s) and its operationalization, and can be used to assess reliability and also different components of validity such as convergent and discriminant validity, predictive validity, etc. This analytical scheme has been employed to test a variety of measurement models in marketing (cf. Bagozzi, 1980) and in other disciplines (cf. Fornell, 1982). Increasingly, this analytical scheme is also being adopted in strategy research for testing measurement models (cf. Farh, Hoffman, & Hegarty, 1984) as well as substantive relationships (cf. Phillips, Chang, & Buzzell, 1983).

Data

The data for this study were drawn from a larger project on the changes and effectiveness of strategic planning systems of large North American Corporations. Data were collected using a structured self-administered mail questionnaire from 202 planning units between February and April 1984. This represents a response rate of nearly 33 percent of the 600 target planning units randomly selected from the Fortune 1000 list of manufacturing and service firms. Table 3 presents some key characteristics of the study sample.

INSERT TABLE 3 ABOUT HERE

Overview of Model Testing

The testing of the operational model involved two steps. First, the adequacy of the two dimensions was independently assessed. Next,

the relationship between the two dimensions was evaluated. Four models were evaluated in this two-step process. The first test (Model 1) aimed at ascertaining the extent to which the 12 indicators reflect the theoretical dimension CAPABILITIES. The second test (Model 2) was a similar examination of the theoretical dimension, OBJECTIVES. Thus, Models 1 and 2 explored the convergent validity of the two dimensions. The third test (Model 3) examined whether these dimensions are indeed distinct dimensions, and this is a test of discriminant validity. Finally, Model 4 examines the nature of the relationship between the two dimensions, i.e., it tested the predictive validity of the two dimensions. The analytical details of testing these models and the results are provided below.

Model 1: Convergent Validity of the CAPABILITIES Dimension

Following Jöreskog's work and conventions of structural equation modeling, this model for convergent validity is written as:

$$X = \Lambda\xi + \delta \quad (1)$$

where X is a vector of P measurements, ξ is a $K < P$ vector of traits, δ is a vector of unique scores (random errors), and Λ is a $P \times K$ matrix of factor loadings. With the assumptions of $E(\xi) = E(\delta) = 0$; $E(\xi\xi') = \phi$, and $E(\delta\delta') = \psi$, the variance-covariance matrix of X can be written as

$$\Sigma = \Lambda\phi\Lambda' + \psi \quad (2)$$

where Σ is the variance-covariance matrix of observations, ϕ is the matrix of intercorrelations among the traits, and ψ is a diagonal

matrix of error variances (θ_{δ}) for the measures. For Model 1, $K=1$, and $P=12$ as shown in Figure 2.

INSERT FIGURE 2 ABOUT HERE

Maximum likelihood parameter estimates (MLE) for Λ , ϕ , ψ , and a χ^2 goodness-of-fit index for the null model implied by equations (1) and (2) can be obtained from the LISREL Program (Jöreskog & Sörbom, 1978). The probability level associated with a given χ^2 statistic indicates the probability (p) of attaining a larger χ^2 value given that the hypothesized model (Figure 2) is supported. The higher the value of p , the better is the fit, and as a rule of thumb, values of $p > 0.10$ are considered as indications of satisfactory fit (Lawley & Maxwell, 1971).

The base model (Figure 2) was estimated using LISREL, and the resulting statistics were: $\chi^2(df:54) = 189.1616$; $p = 0.00$.¹ This indicates that the model as hypothesized in Figure 2 should be rejected. However, exclusive reliance on the χ^2 statistic is criticized for many reasons (cf. Fornell & Larcker, 1981), and researchers increasingly complement this statistic with Bentler and Bonnett's (1980) incremental fit index Δ --which is an indication of the practical significance of the model in explaining the data. The Δ index is represented as follows

$$\Delta = (F_0 - F_k)/F_0 \quad (3)$$

¹A matrix of zero-order correlations of the 18 indicators can be obtained by writing to the first author.

where F_0 = chi-square value obtained from a null model specifying mutual independence among the indicators, and F_k = chi-square value for the specific model. The Δ value for this model was 0.83, indicating that the model should be rejected, since as a rule of thumb Δ should be greater than 0.90 (Bentler & Bonnett, 1980), although some argue that it should ideally exceed 0.95 (Bearden, Sharma & Teel, 1982).

The rejection of the model shown in Figure 2 implies that all the variation and covariation in the measurement of the underlying construct cannot be represented as trait variance plus random error variance only (cf. Bagozzi, 1980). However, an examination of the residual matrix² (the difference between the sample variance-covariance matrix and the model-fitted variance-covariance matrix) indicated that other nonrandom factors may be causing variation in the measurement. As Jöreskog and Sorbom (1979) noted, "...the χ^2 goodness-of-fit-values can be used as follows. If a value of χ^2 is obtained which is large compared to the number of degrees of freedom, the fit may be examined by an inspection of the residuals, that is the discrepancies between observed and reproduced variances and covariances. The result of an analysis in conjunction with subject-matter considerations may suggest ways to relax the model somewhat by introducing more parameters. The new model yields a smaller χ^2 . A larger drop in χ^2 , compared to the difference in degrees of freedom, supports the changes made. On the other hand, a drop in χ^2

²Residual matrices for this model as well as other models tested in this study are not presented here; interested readers may contact the first author.

which is close to the difference in number of degrees of freedom indicates that the improvement in fit is obtained by capitalizing on chance" (emphasis added).

Theoretical justifications can be provided for only eight sets of covariation in error terms, where the entries in the residual matrix exceeded 0.10. These are indicated by (2,1), (3,2) (10,2) (8,3) (6,4) (8,5) (12,6) and (8,7), where numbers refer to the indicators of Exhibit 1. By referring to Exhibit 1, one can readily see that each of these sets of items share a common theme. As an illustration, items 2 and 1 both refer to environmental shifts, while items 3 and 2 reflect a firm's ability to exploit opportunities presented in the environment by adapting to environmental changes. The rationale for introducing such correlated errors into the model is that the original assumption of treating the 12 indicators as independent of one another may be too restrictive, and does not truly represent the underlying model structure (cf. Jöreskog & Sörbom, 1979).

The model presented in Figure 2 was re-estimated by incorporating the additional specification of these eight sets of correlated errors. This model provided a better fit to the data, with the associated model statistics of $\chi^2(df:46) = 62.2686$; $p = 0.0551$; $\Delta = 0.94$. The χ^2_d value was 126.893, statistically significant at $p < 0.01$. A p-value of 0.055 indicates a "marginal" fit and has been previously used to accept models (cf. Bagozzi, 1981; Phillips, Chang, & Buzzell, 1983). The p-value of 0.055, a significant value of χ^2_d , and Δ index of 0.94 all taken together provide strong support to accept this revised model (i.e., Figure 2 with the additional specification of eight sets of correlated errors).

Table 4 presents a summary of the model statistics and the maximum likelihood (ML) parameter estimates for the indicators.

INSERT TABLE 4 ABOUT HERE

An examination of Table 4 indicates that all the factor loadings are significant, using the t-values of the ML estimates. t-values (calculated as ML estimates divided by standard error), greater than 1.96 are generally considered as evidence for the statistical significance of the parameter (cf. Bagozzi, 1980). Additionally, ML estimates can be used to calculate the composite measure reliability (ρ_c) of the dimension (cf. Werts, Linn & Jöreskog, 1974) as follows:

$$\rho_c = \frac{(\sum_{i=1}^n \lambda_i)^2 \text{ var}(A)}{(\sum_{i=1}^n \lambda_i)^2 \text{ var}(A) + \sum \text{ Error Variance}} \quad (4)$$

where, ρ_c = composite measure reliability; n = number of indicators, λ_i is the factor loading relating item i to the underlying theoretical dimension; and var(A) is the variance of the underlying dimension (A) explained by the indicators.

In a practical sense, ρ_c represents the ratio of trait variance to the sum of trait and error variances. ρ_c for this model was 0.887 indicating an acceptable level of measure reliability of the CAPABILITIES dimension (cf. Werts et. al, 1974).

Model 2: Convergent Validity of the OBJECTIVES Dimension

The model for the OBJECTIVES dimension is also based on equations (1) and (2), and is similar to the model for the CAPABILITIES dimension,

except that $P=6$ (see Exhibit 2). The measurement model is diagrammatically represented as Figure 3.

INSERT FIGURE 3 ABOUT HERE

The base model was estimated using LISREL, and the model-testing statistics were: $\chi^2(df:9) = 19.2254$; $p = 0.0234$; $\Delta = 0.927$. An examination of the residuals matrix indicated that the model could be improved by correlating errors between indicators 6 and 5--viz., "evaluating alternatives based on more relevant information," and "avoiding problem areas." The revised model statistics were: $\chi^2(df:8) = 7.7814$; $p = 0.4551$; and $\Delta = 0.97$.³ The three model criteria, viz., a significant value of $\chi^2_d = 11.544$, $p < 0.01$, $p > 0.10$ (Lawley & Maxwell, 1971) and $\Delta > 0.95$ (Bearden et. al, 1982), are all satisfied indicating the acceptance of the model shown in Figure 3 with correlated errors between indicators 6 and 5. Table 5 presents a summary of

INSERT TABLE 5 ABOUT HERE

the model statistics, the ML estimates for the parameters, as well as the value of ρ_c for the model. All the individual model parameters are statistically significant as indicated by the corresponding t-values, being larger than 1.96.

³ An alternative representation to the base model, hypothesizing that OBJECTIVES is a two-dimensional model, with financial objectives and non-financial objectives modeled as separate, but correlated dimensions. The estimation of this model yielded $\chi^2(df:8) = 18.6781$; $p = 0.0167$; $\Delta = 0.930$. The difference between this model and the base model was $\chi^2_d(df:1) = 0.5473$, not significant. Hence the alternative model of separately specifying financial objectives and non-financial objectives was rejected.

Model 3: Discriminant Validity of the Two Dimensions

Thus far, we have treated the hypothesized two dimensions of the model separately and evaluated whether the different indicators reflect the respective dimensions or not. A rival explanation which could be raised at this stage is that these two dimensions are merely sub-dimensions of an overall construct, and that they should not be considered as distinct dimensions. Since the indicators have shades of common meaning, one could conceivably argue that the improvement in system's capabilities and objective fulfillment are not distinct dimensions. In other words, a test of discriminant validity is necessary for rejecting this rival explanation. As noted by Bagozzi (1980), the strongest evidence of discriminant validity is obtained when maximally (conceptually) similar traits are used. Since the two dimensions appear to be conceptually similar, a test of discriminant validity should provide strong support for rejecting the rival explanation that these two dimensions are the same.

Discriminant validity is achieved when the measures of each dimension converge on their corresponding true scores which are unique from other dimensions. Stated differently, it is the degree to which a theoretical dimension in a theoretical system differs from other dimensions in the same theoretical system. This will be achieved when the correlations between the dimensions (ϕ s) are significantly lower than unity. This requires a comparison of a model shown in Figure 4 with a similar model with the correlation (ϕ_{21}) constrained to be equal to unity. A significantly lower χ^2 value for the model with the

unconstrained correlation when compared with the constrained model provides support for discriminant validity. A χ^2 difference value (χ_d^2) with an associated p-value less than 0.05 (cf. Jöreskog, 1971) supports the discriminant validity criterion. Figure 4 represents both models (i.e., constrained and unconstrained) with their model statistics.

INSERT FIGURE 4 ABOUT HERE

As indicated in Figure 4, the χ_d^2 value of 94.1868, $p < 0.001$ strongly supports the discriminant validity hypothesis and thus rejects the rival explanation that the two dimensions are to be treated as one composite dimension. Figure 4 also presents the results of an additional test conducted to eliminate this rival explanation. In this test, an overall composite model represented by 18 indicators was compared with the unconstrained model of Figure 4 that they are two separate, and related dimensions but not one composite dimension. A $\chi_d^2(df:1)$ value of 104.51, $p < 0.001$ further rejects the rival explanations of a composite model. These tests provide strong support to the conceptualization of planning system success in terms of the two separate dimensions as shown in Figure 1.

Model 4: An Examination of Predictive Validity

While a two-dimensional operational model of planning system success has been developed and tested based on criteria of convergent and discriminant validity, the nature of the relationship between the two dimensions has not yet been specifically examined. This can be tested by hypothesizing that an improvement in system's CAPABILITIES will result in higher levels of OBJECTIVE fulfillment, and is termed as an

examination of predictive validity. The theoretical support for expecting such a relationship can be derived from discussions on the central role of strategic planning in realizing organizational objectives (see especially, King & Cleland, 1978; Lorange & Vancil, 1977) as well as the specific notions of system's capabilities (Lorange, 1979) and strategic capability (Lenz, 1980) which influence an organization's strategic actions, which in turn results in the attainment of organizational objectives.

Predictive validity is tested using the model shown in Figure 5. The structural equation for this model is written as:

$$\eta = \Gamma\xi + \zeta \quad (5)$$

where, η = endogenous theoretical construct, Γ = matrix of structural coefficients relating exogenous theoretical construct to endogenous theoretical construct, ζ = residuals of endogenous theoretical construct. The standardized gamma (γ) value of the impact of CAPABILITIES on OBJECTIVES is 0.631 lending strong support to the positive effect of CAPABILITIES on OBJECTIVES. The relatively high value of χ^2 (df 125) = 237.1167, $p = 0.00$, $\Delta = 0.85$ indicates that there are factors in addition to CAPABILITIES which influence the fulfillment of objectives. This is consistent with the theoretical expectation that many facets of strategic planning have important roles in ensuring planning effectiveness. However, since the present focus is on examining the relationship between these two dimensions, rather than modeling planning effectiveness, we focus on the significance of γ_{11} and not on the overall model fit.

INSERT FIGURE 5 ABOUT HERE

DISCUSSION

In this study, we attempted to develop and test an operational model of Planning System Success. The model includes two concepts, viz., (i) improvements in the strategic planning system capabilities and (ii) the extent of fulfillment of key planning objectives. Generic and context-free indicators of CAPABILITIES and OBJECTIVES to develop and test a model which can be applied in large sample studies.

The discussion in this section focuses on four issues. First, the results provide strong support for the measurement properties of the two dimensions. Specifically, the operational model was evaluated in terms of (i) reliability criterion (p_c), (ii) convergent and discriminant validity (models 1, 2, and 3), and (iii) predictive validity (model 4). Since all these criteria were found to be satisfied, the measurement scheme presented here could either be directly employed in future research on strategic planning or can be used as the basis for further refinement and extensions.

Second, it needs mention that the analytical scheme employed here, viz., structural equation modeling approach (Jöreskog & Sörbom, 1978) is not the only available analytical scheme. Although its advantages are apparent in certain research designs (see Bagozzi, 1980, Jöreskog & Sörbom, 1979 for detailed discussions), other analytical schemes are available (e.g., partial least square estimation of Wold, 1982). Further, to aid readers to evaluate the measurement properties, the Cronbach α values for the two dimensions are provided. These are:

CAPABILITIES - 0.871, and OBJECTIVES - 0.748, which indicate acceptable levels of reliability (Nunnally, 1978). In addition, acceptable levels of factor loadings (viz, λ s reported in Tables 1 and 2) augur well for the use of these indicators in future research. However, use of the structural equation modeling approach enables researchers to explicitly model measurement error, correlate measurement errors when theoretically appropriate, and thereby evaluate relationships between theoretical constructs under less restrictive conditions than exploratory factor analysis and ordinary least square regression approaches (see Bagozzi & Phillips, 1982 for a comparative discussion).

The third issue relates to a limitation of the study in terms of employing a single respondent per unit of analysis. Although the respondents were senior-level managers such as Presidents, Vice Presidents - Corporate Planning, and Vice President of functional areas of large corporations (over 60% had sales in excess of \$1 billion--see Exhibit 3), measurement focused at an organization-level of analysis would be better served if data were collected from multiple respondents to assess inter-judge consistency. This is noted as an area for future research.

Fourth, it is believed that the two-dimensional measuring scheme for Planning System Success presented here should be of value and use to other researchers interested in the research stream of strategic planning effectiveness. Although the CAPABILITIES dimension emerged as a strong predictor of objective fulfillment, we urge that both dimensions be employed since they represent different, but related, notions of planning-success. However, measurement schemes are merely first

steps towards testing substantive relationships, and by presenting a set of reliable and valid scales for planning system success, we hope that we would have stimulated some interest among researchers to address a broader and a more important question: What are the key determinants of planning system success? Specifically, it would be interesting and useful to examine if the determinants of the two dimensions are same or not. While it was shown that the capabilities dimension is distinct from the objectives dimension, further support for such a two-level scheme can be derived if the determinants of these dimensions are indeed different.

CONCLUSIONS

By noting that an appropriate operationalization of the theoretical construct of Planning System Success is necessary for theory development and testing in the area of strategic planning systems, this paper developed and tested a two-dimensional measurement scheme. Based on data on the planning practices of 202 planning units, and adopting a data-analytic framework rooted in Jöreskog's analysis of covariance structures, key measurement criteria for the operational model were found to be satisfied. This should serve as a useful guide for future strategy researchers interested in testing various propositions on strategic planning effectiveness, especially the question: What are the key factors that lead to planning system success?

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TABLE 1

KEY CAPABILITIES OF PLANNING SYSTEM^a

1. Ability to anticipate surprises and crises.
2. Flexibility to adapt to unanticipated changes.
3. As a mechanism for identifying new business opportunities.
4. Role in identifying key problem areas.
5. As a tool for managerial motivation.
6. Role in the generation of new ideas.
7. Ability to communicate top management's expectation down the line.
8. As a tool for management control.
9. As a means for fostering organizational learning.
10. Ability to communicate line manager's concerns to the top management.
11. As a mechanism for integrating diverse functions and operations.
12. As a basis for enhancing innovation.

^aEach indicator was measured using a five-point interval scale ranging from much improvement (+2) to much deterioration (-2), to capture the general trend of changes.

TABLE 2

MAJOR OBJECTIVES OF PLANNING SYSTEM^a

1. Enhancing management development.
2. Predicting future trends.
3. Short-term performance.
4. Long-term performance.
5. Evaluating alternatives based on more relevant information.
6. Avoiding problem areas.

^aEach indicator was measured using a five-point interval scale ranging from entirely fulfilled (+2) to entirely unfulfilled (-2).

TABLE 3

Key Characteristics of the Study Sample
(n=202)

1. Level of the Planning Unit

Corporate level	81%
Business unit level	19%

2. Title/Job Position of the Respondent

Planning Responsibility (e.g., Vice President- Corporate Planning)	69.2%
Operating (line) Responsibility (e.g., President, Vice President of functional areas)	30.8%

3. Range of Sales

Less than \$50 million	6.6%
\$51 - \$100 million	4.6%
\$101 - \$250 million	5.1%
\$251 - \$500 million	10.2%
\$501 million - \$1 billion	12.2%
over \$1 billion	61.4%

4. Business Category

Consumer Goods	19.1%
Capital Goods	19.1%
Raw or semi-finished materials	13.1%
Components	9.0%
Service Sector	39.7%

TABLE 4

SUMMARY STATISTICS OF MODEL-TESTING FOR
THE "CAPABILITIES" DIMENSION

(A) Base Model

$\chi^2(df:54) = 189.1616$
p = 0.000
 $\Delta = 0.83$

(B) Model with Correlated Errors

$\chi^2(df:46) = 62.2686$
p = 0.0551
 $\Delta = 0.94$

(C) ML Parameter Estimates

<u>Parameter</u>	<u>ML Estimate</u>	<u>t-value</u>	<u>Standardized Solution</u>
λ_1	1.00*	--	0.504
λ_2	0.996	7.527	0.502
λ_3	1.112	5.888	0.560
λ_4	1.293	6.406	0.651
λ_5	1.431	6.771	0.721
λ_6	1.449	6.799	0.730
λ_7	1.358	6.598	0.684
λ_8	1.209	6.171	0.609
λ_9	1.517	6.962	0.764
λ_{10}	1.239	6.281	0.624
λ_{11}	1.367	6.623	0.689
λ_{12}	1.282	6.378	0.646
ϕ_{11}	0.254	3.633	1.000

*Constrained parameter.

TABLE 5

SUMMARY STATISTICS OF MODEL-TESTING FOR
THE "OBJECTIVES" DIMENSION

(A) Base Model

$$\chi^2(df:9) = 19.2254$$

$$P = 0.0234$$

$$\Delta = 0.927$$

(B) Model with Correlated Errors

$$\chi^2(df:8) = 7.7814$$

$$P = 0.4551$$

$$\Delta = 0.97$$

$$\rho_c = 0.750$$

(C) ML Parameter Estimates

<u>Parameter</u>	<u>ML Estimate</u>	<u>t-value</u>	<u>Standardized Solution</u>
λ_1	1.00*	--	0.717
λ_2	0.804	6.621	0.576
λ_3	0.633	5.386	0.454
λ_4	0.927	7.334	0.665
λ_5	0.751	6.157	0.539
λ_6	0.779	6.363	0.559
ϕ_{11}	0.514	4.996	1.000

*Constrained parameter.

FIGURE 1

PLANNING SYSTEM SUCCESS: A SCHEMATIC REPRESENTATION OF
THE TWO-DIMENSIONAL MODEL

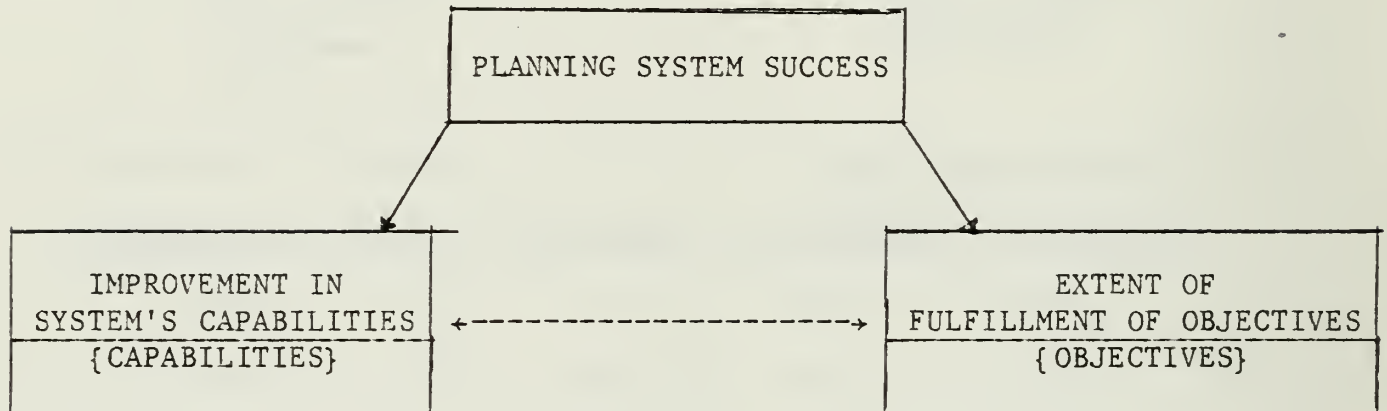
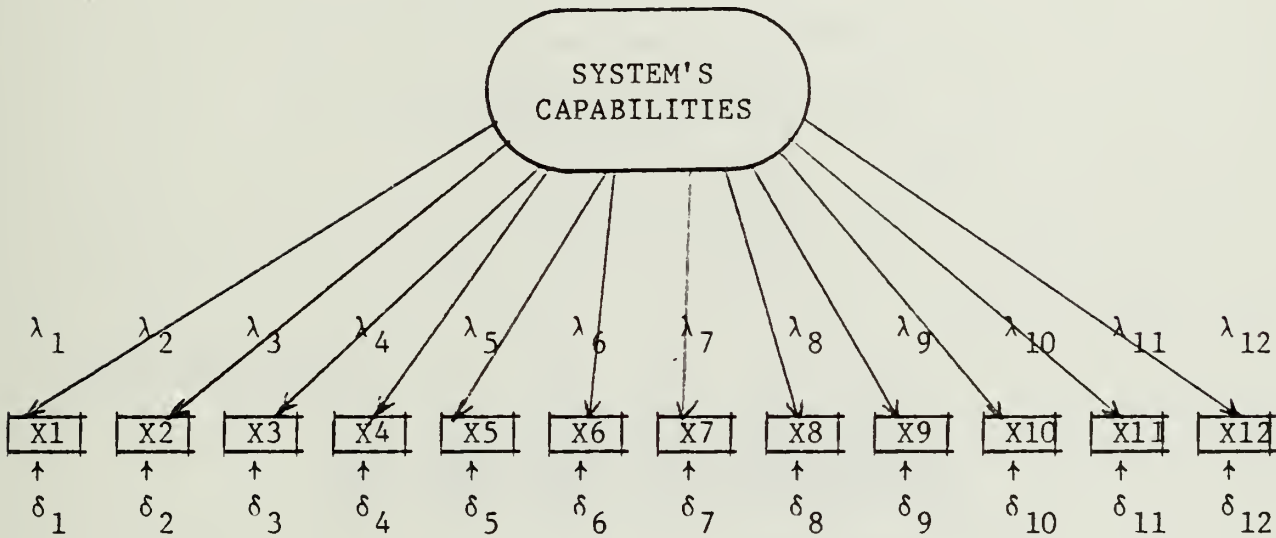


FIGURE 2

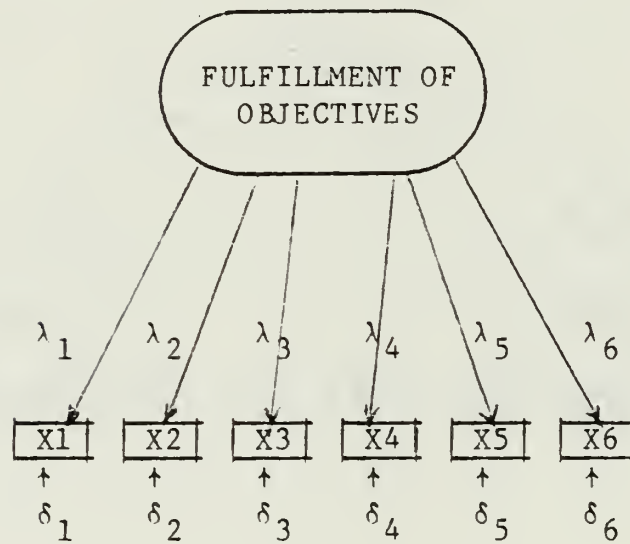
A MODEL OF CONVERGENT VALIDITY OF
THE "CAPABILITIES" DIMENSION^a



^aThe notations of structural equation modeling are followed in the diagram, where the latent (unobservable) variable or theoretical construct is drawn as an ellipse; observable indicators are presented as squares; measurement relations are shown as arrows; error factors are represented as arrows but without origin. λ s represent the degree of correspondence between observed indicators and unobserved theoretical construct.

FIGURE 3

A MODEL OF CONVERGENT VALIDITY OF
THE "OBJECTIVES" DIMENSION^a

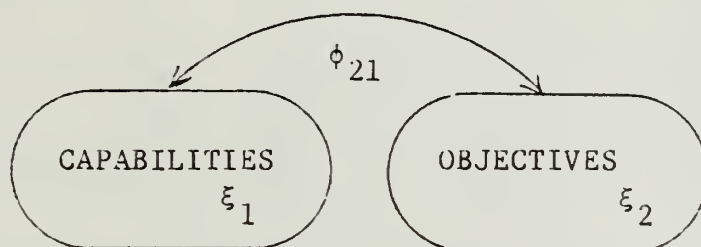


^aFor detailed explanation of the notations, see Figure 2.

FIGURE 4

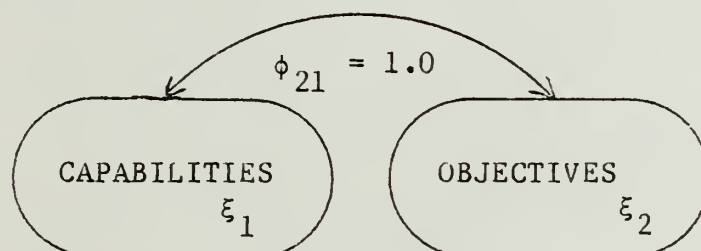
A MODEL OF DISCRIMINANT VALIDITY OF THE
TWO DIMENSIONS

A. Unconstrained Model^a



$$\chi^2(df:125) = 237.1167; p = 0.000; \phi_{21} = 0.631$$

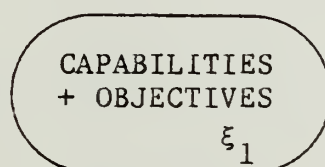
B. Constrained Model



$$\chi^2(df:126) = 331.3035; p = 0.000;$$

$$\chi^2_d(df:1) = 94.1868; p < 0.001 \text{ supports the unconstrained model}$$

C. Alternative Model



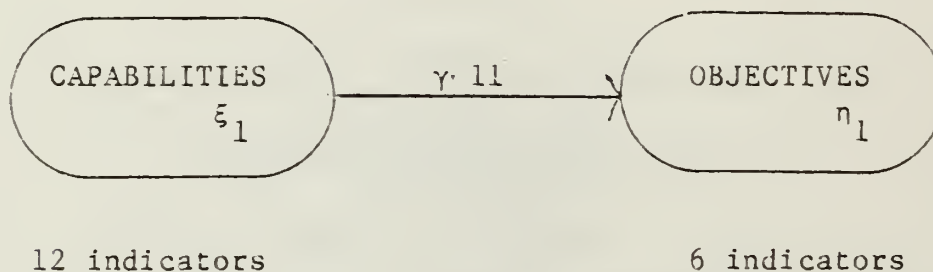
18 indicators

$$\chi^2(df:126) = 341.6312, \\ p = 0.00$$

^aOnly a skeletal diagram is drawn for schematic clarity. The respective models for the two dimensions are the same as shown in Figures 2 and 3 with relevant correlated errors discussed in the text.

FIGURE 5

AN EXAMINATION OF THE PREDICTIVE VALIDITY OF THE TWO DIMENSIONS



$$\chi^2(df:125) = 237.1167;$$
$$p = 0.00$$
$$\Delta = 0.85$$

$$\gamma_{11} = 0.631$$
$$\text{std.}$$

^aOnly the skeletal diagram is drawn for schematic clarity; the respective models for the two dimensions are as shown in Figures 2 and 3 with relevant correlated errors discussed in the text.

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